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Potato plant leaf disease classification using an Enhanced Deep Learning Model

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ABSTRACT

Potato is one of the most important vegetable crops cultivated worldwide, but its production is often threatened by various leaf diseases, particularly early and late blight caused by Alternaria solani and Phytophthora infestans. These diseases can significantly reduce crop yield and quality, and farmers often rely on visually detecting changes in potato leaf color, which can be time-consuming and unreliable. To address this problem, there is a need for computer-aided techniques that can accurately and quickly identify these diseases, even in their early stages. In this paper, we propose a deep learning approach called Enhanced Efficient NET, which uses the Enhanced Efficient NET network to recognize various types of potato leaf disorders. To enhance the model's recognition ability, we introduce a spatial-channel attention method that focuses on the damaged areas. We also address the issue of class-imbalanced samples and improve the model's generalization ability by tuning the EANet model using transfer learning and adding dense layers to enhance its feature selection power. We test the model on a challenging dataset called Plant Village, which contains images taken in diverse and complicated background conditions and achieve an accuracy of 98.12% for classifying various potato plant leaf diseases. Our experiments demonstrate the effectiveness of our approach in robustly tackling distorted samples and classifying potato plant leaf diseases.

Keywords: Classification, Deep learning, Efficient Net, Potato Diseases Blight, Spatial-channel attention, Transfer learning.

Author`s Contribution	Address of Correspondence	Article info.
[1,2,3] Data analysis, interpretation and manuscript writing, Active participation in data collection, Conception, synthesis, planning of research, Interpretation, and discussion	*Wasif Ali* *Email: wasif.ali@uettaxiala.edu.pk*	*Received: June 13, 2022* *Accepted: December 19, 2022* *Published: December 30,2022*

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INTRODUCTION

The FAO predicts that the world's population will reach 9.1 billion by 2050, which will put pressure on food systems to produce more food to meet the growing demand. As a result, it is important for the agriculture industry to continue to innovate and improve food production techniques to ensure that there is enough food to feed the growing population. This could include implementing new technologies and practices such as precision agriculture, genetic engineering, and sustainable farming methods. [1]. In the meantime, the reduction in farmland and the lack of access to pure water inhibit the expansion of nutrient levels. To meet human needs, there is an immediate need to boost food security while using the least amount of growing area. As opposed to this, a number of crop anomalies cause a significant decrease in meal productivity and quality. detection of plant pathogens is crucial to prevent significant damage to agricultural production and to avoid economic uncertainty and food scarcity. Traditional methods of plant assessment rely on the expertise of local professionals, which can be time-consuming and laborious. Moreover, the accuracy of such assessments can vary and may not be highly reliable, leading to potential misdiagnosis of crop disorders. In developing nations with poor incomes, the impact of crop disorders can be particularly devastating, potentially leading to widespread hunger and food insecurity. Therefore, the development of automated and accurate methods for detecting plant pathogens, such as the deep learning approach using Enhanced Efficient NET presented in the previous statement, can help to improve the efficiency and reliability of crop assessment and ultimately contribute to global food security. [2]. Therefore, it is critical to accurately and promptly identify the numerous plant illnesses that might prevent growers from deploying pricey treatment techniques while also improving the food growth rate. The science world is concentrating its effort on the creation of computerized plant illness diagnosis and recognition systems to address the aforementioned issues with manual approaches [3].

Despite the existence of numerous different crops, such as tomatoes, onions, strawberries, and cheerios, among others, the potato plant is a highly consumed crop around the globe. The potato crop is regarded as the major staple by more than a billion people globally and is considered the 3rd largest food on the planet after rice and wheat. More than 300 thousand tons are produced globally each year, providing both nutrients and an essential resource of caloric for people [4]. In addition to providing a sizeable share of the world's nutrition, potatoes are a common source of raw ingredients for industry. Yearly, potatoes are produced all over the world, with the top three exporters being China, India, and Russia [5]. Following a survey performed by the FOA, the prevalence of many illnesses, the majority of those which originate from the leaves of the potato crop and cause a reduction in output amount from 9% to 11% annually [6], is the main obstacle to the pace of potato growth. To examine potato crop leaf disorders, the scientific world initially used methods from the fields of biological sciences and cell biology [7, 8]. These methods, however, exhibit a high processing complexity and demand a significant need for expert skills [9].

The deep learning (DL) techniques are currently being evaluated primarily to address the shortcomings of ML algorithms. Different DL methodologies, including CNN [10], RNNs [11], and long short-term memory (LSTM) [12], are currently widely praised in the field of food security. The DL methods are capable of accurately estimating the informative collection of sample features characteristics without the assistance of domain experts. Both these strategies for object recognition and deep learning (DL) imitate how the human brain functions when a person locates and recognizes a variety of items by looking at examples of them. DL approaches provide reliable results in the field of modern agriculture research and are effectively suited to a variety of jobs, whereas different kinds of deep neural networks (DNNs) exhibit greater precision than multispectral evaluation [20].

Our approach can accurately classify various types of potato plant leaf diseases, even in their early stages, which is crucial for early detection and effective control of these diseases. The spatial-channel attention method incorporated in our model helps to enhance the recognition ability by focusing on the damaged areas, overcoming the challenges posed by lighting fluctuations, distortion, and blurring in the images. Furthermore, transfer learning is employed to address the issue of class-imbalanced samples and improve the generalization ability of the model. The performance of our approach is evaluated on a challenging dataset called plant Village, which contains images taken in diverse and complicated background conditions. Our model achieved an impressive accuracy of 98.12% in classifying various potato plant leaf diseases, demonstrating its effectiveness in tackling the problem of potato plant disease classification. Besides, the AM strategy improves the recall power of the proposed solution by passing relevant details of the noticeable attributes like disease areas of plant leaves. The distinctive contributions of this work are elaborated as:

- The proposed Enhanced Efficient NET model is tested on the plant Village dataset, which is a challenging and open dataset containing images with various background conditions, lighting changes, and color variations. The model achieved an accuracy of 98.12% for the classification of various potato plant leaf diseases, which demonstrates its effectiveness in potato plant disease diagnosis.
- The development of computer-aided techniques, such as Enhanced Efficient NET, can significantly reduce the time and effort required for potato plant disease identification, thereby improving agricultural productivity, and reducing economic losses.

The rest of the paper is structured as follows: Section 2 presents an overview of related work in this area, while Section 3 describes our proposed method. In Section 4, we present and discuss the results obtained from our experiments. Finally, Section 5 provides a conclusion of our work and outlines potential avenues for future research.

LITERATURE REVIEW

Bhagat et al. [13] authors utilized BoWs and SURF-based techniques for identifying potato leaf diseases. They first used the bag of word approach for feature extraction, followed by the SURF method to extract strong features. These features were then passed to an SVM for classification. The experiments were conducted on potato leaves from the Plant Village dataset and achieved an accuracy of 97%. The method in [13], performed well however model didn't consider unseen or real-world samples. In this [14], authors of this study utilized the ResNet50 CNN pretrained model for the purpose of detecting and classifying plant diseases. Specifically, they applied this approach to potato leaves obtained from the Plant Village dataset, using augmentation and segmentation techniques prior to passing the data to the ResNet-50 model for classification. The proposed method achieved an impressive accuracy rate of 98%. The method performed well however its accuracy depends on the augmentation and needs further improvements.

In [15], Kang et al. proposed the lightweight CNN-based approach for the recognition of potato leaf diseases. The authors utilized multi-scale pyramid fusion technology for efficient feature selection. This fusion of these features was achieved using the improved backbone model and optimized features. This lightweight technique recognized the plant leaf disease identification and achieved 93% accuracy. However, the presented model needs further improvements in accuracy. Pal et al. [16] proposed the AgriDet approach, which stands for Agriculture Detection. This method used the traditional Inception-Visual Geometry Group Network and Kohonen for identifying potato leaf disease. To address the occlusion problem, a multi-variate grab cut was applied. The proposed method was tested on the Plant Village dataset for detecting and segmenting potato leaf diseases. The model achieved good results with an accuracy of 92.12%. The approach incorporated a dropout layer to handle the overfitting issue. However, it could not detect multiple occurrences of the same disease in a single image.

To detect and classify the potato leaves, Kumar et al. [17] proposed an automated method for potato leaf disease classification, based on Gaussian filtering and Fuzzy c-means clustering. The method involved the extraction of different types of features, including textual, geometrical, and statistical features. These features were then passed through PCA for efficient feature selection. Finally, various classifiers were used for the classification of potato leaves. The proposed method achieved an accuracy of 92.89% on the plant Village dataset, demonstrating its effectiveness in detecting potato leaf diseases.

Rashid et al. [18] presented a multi-level deep learning-based model for potato leaf disease recognition. The proposed approach involved YOLOv5 for image segmentation and a deep CNN model for potato leaf identification. The model was tested on a proprietary dataset and achieved promising results. However, it was limited in detecting multiple diseases from a single image. Tiwari et al. [19] proposed a deep learning technique for detecting potato leaf diseases, which involved feature extraction using the VGG19 model, followed by classification using various classifiers. The logistic regression classifier performed the best, achieving 97.8% accuracy on the Plantvillage dataset. However, the presented model needs further improvements to better detect unseen examples. Similarly, a CNN approach was utilized in [20] to recognize potato leaf diseases. The technique was based on the Adam optimizer and cross-entropy for model analysis. The final classification was performed using the softmax layer. Another CNN-based approach was employed in [21] for the detection of potato leaf diseases. The experimentation was performed on the Kaggle dataset and attained 97% accuracy. However, the presented model tackles only binary classification. Iqbal et al. [22] proposed a method for the segmentation and classification of potato leaf diseases. The Plant Village dataset was utilized for the evaluation of the proposed technique. A deep learning technique based on the DenseNet approach was proposed for potato leaf disease detection using the PlantVillage dataset. proposed a method that combines segmentation and classification for potato leaf diseases using the Plant Village dataset. The method uses random forest for binary classification of healthy and diseased leaves with an accuracy of 97%.

The model achieved 97.2% accuracy, but it is computationally complex and requires more time for processing [23]. The model was based on the DenseNet approach which was then modified using the addition of a layer in the model. The model achieved 97.2% accuracy for the classification of potato leaf disease. However, this model is computationally complex in terms of time. In [24], the authors presented the deep learning-based approach for the classification of potato leaf diseases. The proposed technique was based on four types of models like MobileNet, VGG16, VGG19, and ResNet. Fine-tuning of parameters was performed to enhance the accuracy of the proposed model. The experiments were performed on the PlantVillage dataset and achieved 97.8% accuracy. However, the presented approach did not tackle the real-world samples.

RESEARCH METHODOLOGY

Our proposed work is based on the EfficientNET approach called improved Enhanced EfficientNET for the recognition and classification of potato leaf diseases. The improved model has additional layers at the bottom of the model which are helpful to enhance performance. The complete flow of our improved model is shown in Fig 1. The overall process is explained in algorithm 1.

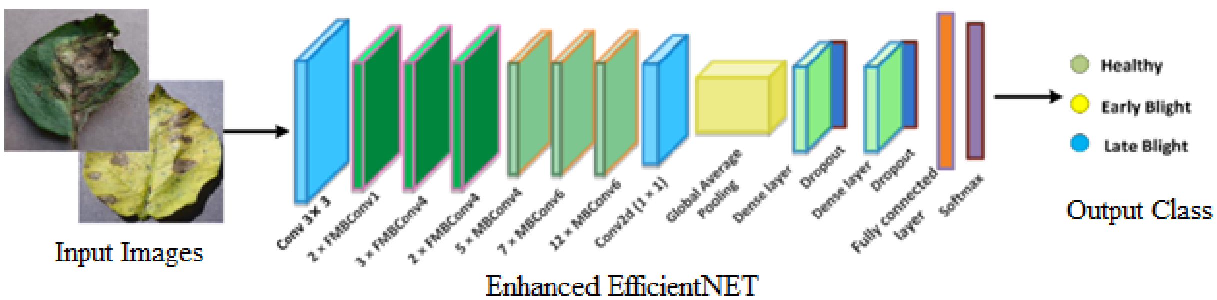

Figure 1. Flow of the Proposed framework

Dense deep learning (DL) networks, such as DenseNet, can help in extracting and learning more effective features from images. These features can then be used to improve the classification performance of the model. DenseNet is particularly effective because it connects all the layers in a dense block, allowing the network to access all the previously learned features, which can improve the feature reuse and reduce the vanishing-gradient problem. Additionally, these networks can learn more complex and abstract features from the input images, which can lead to higher accuracy in classification tasks. [16]. The deployment of these CNN techniques depends heavily on the availability of processing power and memory needs, which places a computational constraint on the models when deep networks are used. This issue is to optimize the architecture and parameters of the CNN models to strike a balance between classification accuracy and computational efficiency. This can be achieved through techniques such as network pruning, parameter sharing, and quantization. Additionally, hardware improvements such as the use of graphics processing units (GPUs) can also help to accelerate the computation of deep learning models. Another approach is to use transfer learning, where pre-trained models are fine-tuned on new data to reduce the need for extensive training on large datasets. [34]. In this study, we introduced a simple and reliable computational strategy to improve model performance for categorizing various anomalies.

Algorithm 1: Steps for potato plant leaves abnormalities categorization
Input:
TP (total potato images with various abnormalities)
Labels (class of each potato sample)
Output:
The category of potato plant leaf diseased region
Enhanced EfficientNET (improved EfficientNet-model)
Data preparation:
Define SampleDimension as [j,h]
Retrieve labels associated with each input sample using ReadClassLabel(TP, Labels)
Training phase:
Define two functions:
EffiNetV2(), which measures the keypoints with Enhanced EfficientNET network
EvaluatFramework(), which accomplishes the model training
Train the improved Enhanced EfficientNET model using EffiNetV2(SampleDimension, Labels)
Distribute the database into TrainingPart and TestPart
For each sample c in TrainingPart:
Compute the improved-EfficientNet features using →tm
Utilize tm images for Enhanced EfficientNET training and calculate time
Identify the label of the affected area of the potato leaf using IdentifyPotatoLeafAffectedAreaLabel(tm) and store in £abelA
Evaluate the model using EvaluatFramework(improved-EfficientNet, LoclizeA) and store in Ap
Test phase:
For each image C in TestPart:
Compute features using the trained model Enhanced EfficientNET and store in βC
Predict the category of the potato plant leaf diseased region and its confidence score using Predict(βC) and store in [ConfidenceScore, ClassLabel]
Show the sample's ClassLabel
Exit

The Enhanced EfficientNET model is trained using a dataset of potato plant images with various abnormalities and associated class labels. During the training phase, the model is trained to measure the key points with the EfficientNetV2 network and accomplish the model training using the Evaluat Framework function. The dataset is split into training and testing parts, and the improved EfficientNetV2 features are computed for each sample in the training part. The computer features are then utilized to train the Enhanced EfficientNET model, and the time is calculated for the training process. The Identify Potato Leaf Affected Area Label function is used to identify the potato leaf affected area label, and the Evaluat Framework function is employed to evaluate the model using the improved EfficientNetV2 and the identified labels. During the test phase, the model predicts the class label of each image in the test part by computing features using the trained model and employing the Predict function. Finally, the predicted class labels are displayed as output.

RESULTS

This section would be helpful to have more specific information on the dataset used, the performance measures employed, and the comparison models that were evaluated in order to provide a more detailed response. It also illustrates used performance measures. Moreover, we have executed a huge result comparison with various models to show the effectiveness of our approach.

Dataset

The recognition ability of our framework tested at PlantVillage [45]. Tthe dataset used to train and evaluate the classification results of the proposed technique is called the PlantVillage repository, which contains a large collection of plant leaf images, including 54,306 images of 14 types. However, for this particular study, only a sample of potato plant leaf images from this dataset is used for performance evaluation. The PlantVillage dataset was chosen because it includes samples with varying characteristics such as size, structure, and orientation, as well as various distortions such as clutter, blur, intensity, and color variations. The dataset is free and available online for model simulation. Fig 2 shows a few samples from this dataset.

Figure 2. PlantVillage Dataset samples

Precision and recall are standard performance metrics used to evaluate classification results. Precision measures the percentage of correctly classified instances in a predicted class, while recall measures the percentage of correctly classified instances in a given class out of all instances of that class in the dataset.

In the first phase of model evaluation, the performance of the proposed strategy was tested in terms of class-wise results to check how well it can recognize various types of potato plant leaf abnormalities. The attained values were reported for all three classes, namely healthy, early blight, and late blight, in Fig. 3. The results indicate that the approach was able to recognize all three classes effectively.

Specifically, the precision results were 98.26%, 98.03%, and 97.99% for healthy, early blight, and late blight, respectively. The recall values were 97.41%, 97.15%, and 97.10% for healthy, early blight, and late blight, respectively. These values suggest that the proposed approach achieved high accuracy in recognizing the potato plant leaf abnormalities.

Our proposed approach has shown promising results in classifying potato plant leaf diseases. The precision and recall scores of over 97% for all three classes indicate that the model can effectively recognize the different types of abnormalities in potato crops. The confusion matrix also confirms that the model has shown better values for all three classes, with a minimum error rate of 97.22%.

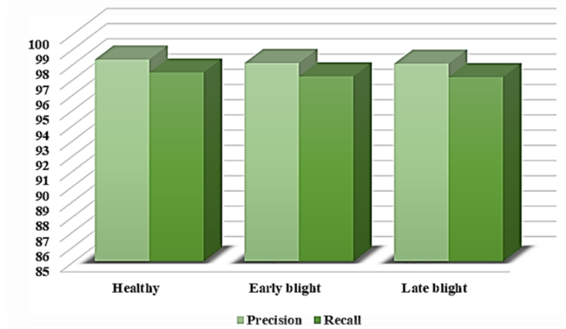

Figure 3. Results attained precision, and recall

It is also interesting to note that your approach's better classification behavior is attributed to the computation of relevant and distinctive sample characteristics. This demonstrates the importance of feature extraction and selection in improving the performance of machine learning models.

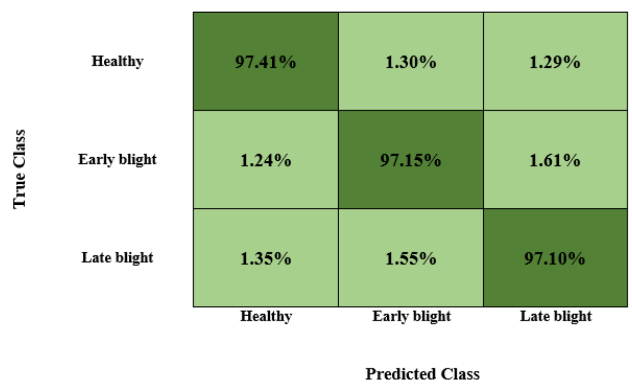

Figure 4: Attained results in form of the confusion matrix

The comparative analysis presented in Table 2 clearly shows that the proposed approach outperforms other DL frameworks in terms of both accuracy and model size. The proposed approach has the least number of model parameters, which makes it computationally efficient and reduces the risk of overfitting. On the other hand, the comparative techniques have a higher number of model parameters, which can cause overfitting issues and result in poorer performance. The pixel and channel attention approach adopted by the proposed technique during feature computation is an innovative way to enhance the recognition ability of the model. This approach helps in identifying the most relevant and distinctive set of image characteristics, which results in better classification performance. In conclusion, the proposed approach presents an efficient and effective solution for classifying various types of potato plant leaf diseases. The comparative analysis clearly shows that the proposed approach outperforms other DL frameworks in terms of both accuracy and model size, which makes it a promising solution for practical applications.

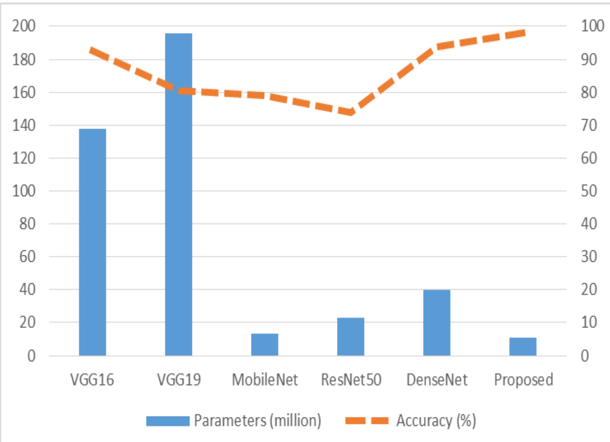

Figure 5: Assessment of the suggested approach with DL models

The main reasons for the better performance of your approach compared to the comparative techniques. The lighter structure of your model helps to avoid overfitting, while the pixel and channel attention approach and the additional layers at the end of the network structure help to better identify the relevant image characteristics and improve the classification score. These are all important factors to consider when developing a DL approach for image classification tasks.

CONCLUSION

The Enhanced EfficientNET approach presented in this work is a promising solution for classifying various types of potato plant leaves. The addition of the AM strategy and extra layers at the end of the model structure, in conjunction with an end-to-end learning mechanism, helps the model robustly extract high-level signs of infected regions and associate them with related groups. The rigorous experimentation conducted on the PlantVillage dataset demonstrates the effectiveness of the approach, particularly in recognizing potato diseases from distorted images. We have accomplished rigorous experimentation on a complex data sample designated as the PlantVillage to show the effectiveness of our framework and proved through the attained performance scores. The better performance of your approach compared to the comparative techniques. The lighter structure of your model helps to avoid overfitting, while the pixel and channel attention approach and the additional layers at the end of the network structure help to better identify the relevant image characteristics and improve the classification score. In the future it would be interesting to see how the Enhanced EfficientNET approach performs on other challenging datasets. This could help determine the generalizability of the model and its potential applications in other domains beyond plant pathology.

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